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SYNERGIES BETWEEN LEAN CONSTRUCTION AND ARTIFICIAL INTELLIGENCE: AI DRIVEN CONTINUOUS IMPROVEMENT PROCESS

Diego Cisterna[1], Svenja Lauble[2], Shervin Haghsheno[3] and Jan Wolber[4]

ABSTRACT

Both, Lean Construction (LC) techniques and Artificial Intelligence (AI) methods strive for the continuous improvement of production systems in projects and organizations. A combined implementation of both approaches is an ongoing research area. Therefore, the question arises as to whether the added value generated by implementing both approaches jointly is greater than the added value generated by implementing them independently and what is the significance of people in their combined use.

This paper explores theoretically the potential of synergies between LC and AI in the AEC sector with exemplary use cases as well as their resulting effects. Humans play a crucial role as interface between a combined use of both of them. As a result, a framework containing LC, AI and people is formed as basis for further combined developments. Therefore, change management, an area in which Lean has spent several years developing, can help both approaches gain traction. With the results, targeted applications can be developed, and practice can be supported.

KEYWORDS

Lean construction, artificial intelligence, continuous improvement, integration, cultural change

INTRODUCTION

With the industrial revolution, humans have been increasingly physically relieved in many ecosystems by machines and took the lead role of the production system. In this context, Lean techniques supports not only the continuous improvement of the production system by avoiding waste, but also the optimization of the interaction between humans

[1] Research Fellow. Karlsruhe Institute of Technology (KIT), Institute of Technology and Management in Construction, 76131 Karlsruhe, Germany. Phone +49 (0)721 608 45476, diego.cisterna@kit.edu, orcid.org/0000-0003-4282-1141

[2] Research Fellow. Karlsruhe Institute of Technology (KIT), Institute of Technology and Management in Construction, 76131 Karlsruhe, Germany. Phone +49 (0)721 608 41513, svenja.lauble@kit.edu, orcid.org/0000-0002-0376-1791

[3] Professor. Karlsruhe Institute of Technology (KIT), Institute of Technology and Management in Construction, 76131 Karlsruhe, Germany. Phone +49 (0)721 608 42646, shervin.haghsheno@kit.edu, orcid.org/0000-0002-0602-6370

[4] Research Fellow. Karlsruhe Institute of Technology (KIT), Institute of Technology and Management in Construction, 76131 Karlsruhe, Germany. Phone +49 (0)721 608 41513, jan.wolber@kit.edu, orcid.org/0000-0002-7374-1585

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and machines. Following, humans are recentered in the focus. Today, the application of Lean techniques to construction (Lean Construction) plays a crucial role on many construction sites as with them processes can be stabilized and continuously improved.

In contrast, with the growing available amount of data and computing power, methods of Artificial Intelligence (AI) are a newer field in the AEC industry. AI use cases in construction are for example generative design (Chase, 2005), predicting construction durations (Petruseva et al., 2013) or costs (Wilmot & Mei, 2005), detecting the construction progress (Dimitrov & Golparvar-Fard, 2014) or hazards on construction sites with image recognition processes (Seo et al., 2015). These use cases show that AI models also strive to improve existing processes towards a higher level of predictability, sustainability, or transparency. Here, humans are increasingly mentally relieved.

Lean Management techniques and AI elements are strongly linked: "*Just as the introduction of Lean Management has driven profound cultural changes in corporate culture, the introduction of AI in manufacturing processes requires its own cultural adaptation to which Lean Management must play a critical role*" (Four Principles, 2019).

By doing this, our proposition is that potential synergies can be leveraged and the role of humans in mental and physical processes focused. Few research papers so far analyze the potential synergies between both fields: Lean Construction (LC) and AI. Vickranth et al. (2019) analyze potentials of Lean techniques, AI in Construction as well as Enterprise Resource Planning to involve these fields in construction projects. Here, the authors supposed to integrate AI tools in the monitoring phase, while to implement Lean techniques in the planning phase. These detached observation of AI and LC does not show the potential synergies. Arroyo et al. (2021) describe AI use cases in construction and emphasize the crucial role of ethical and social aspects in the AI development. The authors conclude that the use cases must be well considered so that a deep process understanding is not lost by a pure outsourcing to AI models and humans are still a central aspect. They identify that there are potential synergies between both fields without a closer consideration.

Following synergies between both fields are so far not systematically elaborated and use cases involving both fields are not summarized. **Therefore, the question arises as to whether there are synergies between the two fields that result in more added value when both approaches are applied together than by applying them independently and what role people play in their combined use**.

In this paper potential synergies between Lean Construction and AI will be analyzed. Accordingly, both fields will be first described. Following, use cases involving Lean Construction techniques and AI elements are systematically explored. As a result, a framework containing both fields and the human factor will be created.

BACKGROUND

LEAN MANAGEMENT

Lean management refers to a philosophy with values, principles, methods, and tools with the aim of eliminating or reducing waste and focusing on customer needs (Bertagnolli, 2018).

Lean management has its origins in Toyota's production system. The term Lean was first mentioned in the book "The machine that changed the world" (Womack et al., 1991) and further developed as a philosophy in "Lean Thinking" (Womack & Jones, 2003).

Today, the approaches of Lean Thinking are implemented in a wide variety of industries such as construction.

Lean thinking approaches consist of five principles: identify the value to the customer, define the value stream, apply the flow and pull principle, and strive for perfection (Womack and Jones 2003).

Salem et al. (2006) compiles essential lean techniques with their principles. These techniques do not represent a conclusive summary, but rather serve as an exemplary framework for the present work. This study was selected as a LC framework because the author contrasts, in his research the techniques developed for lean construction with those developed for lean manufacturing, where IA is more widespread.

Table 1: Lean Implementation Tools (Table 1 in Salem et al., 2006, adapted)

Scope	Technique	Scope	Technique
Flow variability	Last Planner System® (LPS)	Transparency	Five S's
	Takt-planning and Takt-control		Increased visualization
Process variability	Fail safe for quality	Continuous improvement	Huddle meetings
			First run studies

LEAN CONSTRUCTION AND ITS TECHNIQUES

Lean Construction is the adaptation of Lean principles derived from the Toyota Production System into the construction sector. (Salem et al., 2006)

Last Planner System® (LPS)

The Last Planner System describes an incremental method for process planning with the inclusion of the last planners or foremen. Starting from the framework schedule, the planning is refined step by step up to a 6-week forecast. In the control system, key figures are included with the aim of the Continuous Improvement Process (CIP), such as the Percentage Plan Complete (PPC). (Ballard)

Takt-planning and Takt-control

In Takt-planning, the process plan is divided into a spatial, temporal and content dimension with the aim of stable realization and clear presentation. In the cycle control, the plan is adjusted together with the foremen and key figures for the CIP are included.

Fail safe for quality

Fail safe for quality summarizes techniques for controlling quality and safety issues. This includes Gemba walks with action lists.

Five S's

The five S's include the steps: Sort, Straighten, Standardize, Shine and Sustain. This pursues the goal of maintaining the cleanliness and a systematic workplace organization.

Increased visualization

Commitment charts, mobile signs, Kanban cards or projects milestones can be used for visualization. The goal of these is to increase attention to deviations, for example.

Huddle meetings

Huddle or stand-up meetings are short, sharp, focused, daily team meetings with foremen (see last planner) to discuss overlapping activities or challenges on the jobsite. Also,

huddle meetings include daily meetings with site personnel to discuss the day's activities, items related to safety or order and cleanliness.

First run studies (PDCA cycle)

First run studies are carried out according to the four steps Plan, Do, Check, Act (PDCA). In this way, new methods, a modified process sequence or a redesign of the crew can be tested in their implementation.

Continuous Improvement Process (CIP)

Figure 1 summarizes the Continuous Improvement Process (CIP) as the principle to strive for perfection. After a first implementation of one of the mentioned Lean techniques, Key Performance Indicators (KPIs) are defined as metric to systematically measure and track the CIP. These KPIs can also be part of the project’s documentation. They support the observability and transparency. As a positive result of implementing the Lean technique, waste is reduced, and the client value is enhanced. The KPIs and with it the project improves, so that more and more people begin to apply this Lean technique. Finally, as a result of this beneficial effect, additional Lean practices will be deployed, triggering another evolution in the cycle.

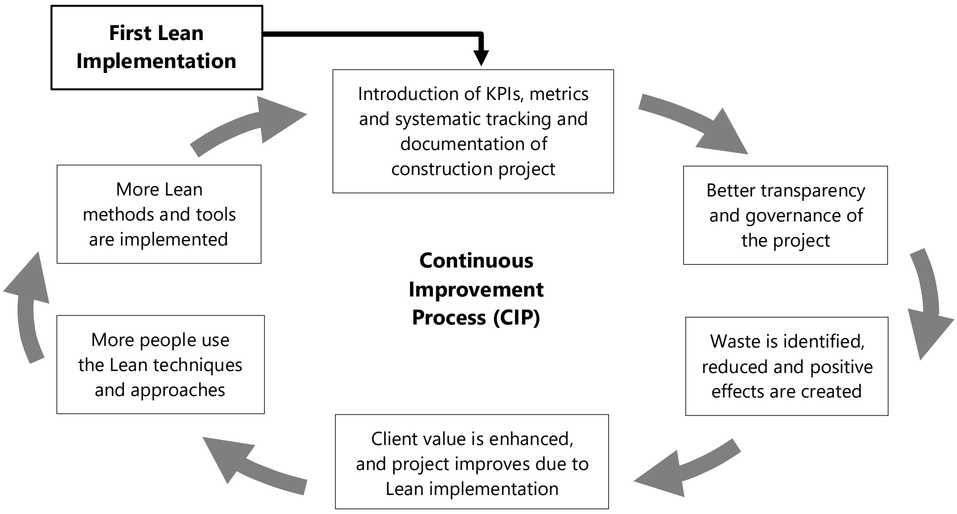

Figure 1: The Lean virtuous cycle (based on the five lean principles of Womack and Jones (2003))

ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) is a field of research within computer science that deals with the development of intelligent machines and computer programs. Since its origins in the 1960s, a multitude of technical developments have led to the fact that the results of this field of research are nowadays an integral part of our everyday life. They are used in autonomous driving, in medicine, but also in many other areas of our daily lives.

Historically, the foundations for this were laid by the British mathematician Alan Turing in 1936. In 1955, John McCarthy was one of the first to define AI as machines that behave as if they had intelligence (Ertel, 2016). In contrast, since natural intelligence includes consciousness, emotionality, and intuition in addition to complex cognitive abilities, the following definition for AI fits better: artificial intelligence "[...] gives computers the ability to learn without being explicitly programmed." (Samuel, 1959)

Over the years, two subfields within AI research have emerged as particularly promising. These are the area of Machine Learning (ML) and Deep Learning (DL). Here, ML is a subset of AI and DL is a subset of ML (Wittpahl, 2019). Common to both subsets are the idea of learning patterns from data and thus generating knowledge from experience. In this way, a system can subsequently apply the self-acquired knowledge representation to process unknown tasks of the same type (Döbel et al., 2018).

Within these categories that comprise AI frameworks are designed to handle specific challenges. There are several frameworks for identifying unknown patterns in various forms of data. These include Computer Vision, which recognizes objects in images, Natural Language Processing (NLP), which recognizes words in text and in audio, and Data Analytics, which analyses massive amounts of data. For instance, there are frameworks for developing “Expert Systems” that are based on decision trees. There are also other frameworks that use a combination of the above mentioned to be applied in Robotics or in the Creation of Virtual assistants such as “Chatbots”.

Guo (2017) defines seven steps for the application of AI:

1. Data collection: The first step significantly influences the outcome of the learning process, depending on the quality and quantity of the data collected (Guo, 2017). Formally, a sample is taken here from a population, which should therefore be as representative as possible.

2. Data preparation: After the desired data has been collected, it must be prepared and organized in different ways depending on the algorithm used. Data preparation often takes up most of the time in the machine learning process (Webb, 2010). To test the model after learning, the existing data is divided into training data and testing data (Ertel, 2016). A typical example of this step is the labelling of photos to train computer vision models.

3. Framework/Model selection: With the target to learn with the data thus prepared, a choice of model must now be made. This is partly dictated by the framework of the problem, the type of input and output data or the number of features. Last but not least, it also depends on the experience and intuition of the programmer. A newer research area in AI is explainable AI (XAI) to solve some ethical and social aspects within a growing complexity. ‘Human in the Loop’ contains the integration of humans in the above-mentioned steps such with an appropriate design and KPIs. Also, Schia et al. (2019) states that “the human-AI trust will be the most decisive factor for a successful implementation.”

4. Training: After the steps of the preparation now the actual successive learning process of the model begins. Based on the data provided, an approximation is sought by gradually adapting the model to the data using the feedback signal (Chollet, 2018).

5. Evaluation: After training the model, the learning success must be verified using the generalization capability with performance indicators such as the MAE (Mean Absolute Error).

6. Parameter optimization: In this step, hyperparameters that are fixed at the beginning of the models are adjusted (VanderPlas, 2016). Adjusting the parameters can substantially improve the learning outcome, if necessary.

7. Deployment: Once all adjustments to the model have been made, it is ready for deployment. Here, the human factor becomes relevant as employees and the management must be involved and convinced to carry out a successful change management.

Continuous Improvement of AI

Figure 2 shows the cycle how AI models can continuously be improved. With the deployment of an AI model in construction supporting the people in their work, the project improves. As more people utilize the AI model, more data is generated. This extra data enables more accurate predictions, and the model improves as result.

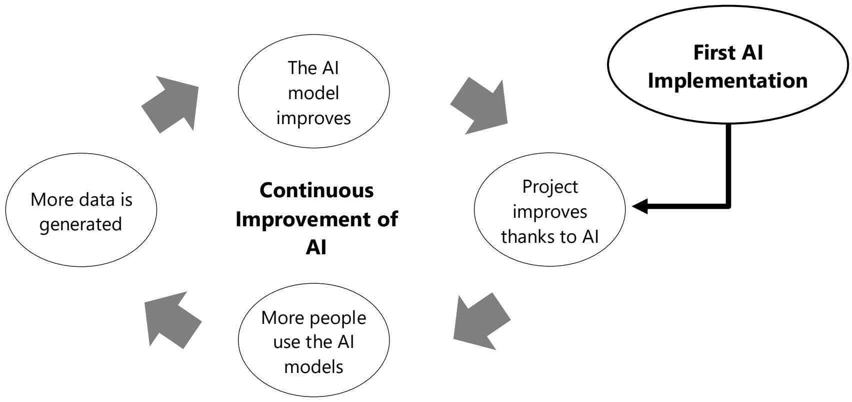

Figure 2: The AI virtuous cycle (Figure 9.9 in Mauro and Valigi (2020), adapted)

METHODOLOGY

To be able to profit from potential synergies between the two topics of Artificial Intelligence (AI) and Lean Construction (LC), there must be a motivation for the people involved. Synergy is understood to be when "[...] through the interaction or combination of factors, a different, e.g., greater effect is achieved than corresponds to the sum of the separate, independent individual effects" (Ebert, 1998). The following procedure according to Ehrensberger (1993) is used to systematically determine synergies. This consists of four steps:

1. The **problem area** of the jointly used concepts is to be identified.
2. **Synergy processes** are to be identified. In these synergy processes, the basic concepts are to be identified as in step 3 and 4 described.
3. In them, the **basic effects** and their **subsequent effects** resulting from the synergies are to be classified in the following five dimensions: **Quality**, **Time**, **Quantity**, **Type** and **Space** dimension and to be evaluated.
4. The synergies are to be classified in an **interaction-oriented framework** to further define the context of consideration. These consist of **Strategic**, **Organizational**, **Cultural** and **Community** dimensions.

The identification of the synergies and the classification of their effects and type of interaction in their different dimensions is carried out jointly in brainstorming workshops with experts in AI and LC from the German research project “Smart Design and Construction” (SDaC). This project which integrates AI approaches into the AEC industry, consists of more than 40 partners from the construction sector, IT industry, and research organizations.

At the end, the results are synthesized in a framework for the interplay between LC and AI.

RESULTS

Step 1: Identification of the problem area: The goal is to identify the synergies of both topics AI and LC in their mutual application. In both topics the continuous improvement process (CIP) of the existing production system is a core element. Thus, the goal is not to analyze a specific method or technique from one of the two topics in more detail. The target is to examine the synergies of the CIP with both topics.

Step 2: Identification of synergy processes: On the one hand, the LC techniques according to Salem et al. (2006) and the (sub)processes required for this are analyzed. On the other hand, data collection and data preparation are particularly time-consuming when applying AI methods. These two steps are therefore also the focus of the synergy analysis.

Step 3 and 4: Identification of effects and interaction-oriented framework: Following Ehrensberger's procedure, it was found that the interplay between LC and AI revealed both effects and interaction-oriented dimensions. As a result, it became possible to find synergies between LC and AI in all Lean techniques defined by Salem et al. (2006) and in steps 1, 2, 5 and 7 of the seven steps for implementing AI defined by Guo (2017).

Table 2 shows the AI processes that are supported by LC techniques, while Table 3 shows the LC techniques that are supported by AI models. Both Tables list examples of synergies between AI and LC that can be deployed at the process and technology domains of a project (see Figure 3). The classifications were generated based on the expertise of AI and LC specialists and the results of prototyping nine AI applications in AEC environments between 2020 and 2022 as part of the SDaC project.

Table 2: Synergic interactions in which Lean supports AI Processes

AI Process	Synergy with LC techniques	Effect(s)	Interaction-oriented dimensions
Data collection	**Data to train AI Models** With LC techniques, metrics and KPIs (e.g., PPC) are introduced. Time series are recorded by a systematic tracking and documentation of the construction project	**Quantity** (More data is generated through people)	**Community** (People generate the data)
Data preparation	**Structured data & KPIs** 5S can be used not only to organize physical assets, but also data. It can be applied in data preparation, as it allows to classify (sorting) data, standardizing data categories, filtering out (shine) data outliers and sustain the data structures	**Quality** (Structured data & KPIs)	**Organizational** (Structure of data)
Evaluation	**Validation of AI model** Model performance validation and setting a basis for model optimization can be compared to PDCA's "Check" and "Act" steps. Visualization and interpretation support model validation (e.g., Mean absolute error (MAE), Shapely Framework). Further on, with the "5 Whys" method the evaluation result can be challenged.	**Quality** (Better observability and governance of the project)	**Strategic** (Definition and evaluation of objectives for the AI)
Deployment	**Change management** With Lean techniques concerns are tracked, people and management involved in the implementation process: e.g., PDCA support tracking the implementation, in huddle meetings the deployment can be discussed	**Quantity** (More people using the AI-model)	**Cultural** (Change Management)

Table 3: Synergic interactions in which AI supports Lean Techniques

LC Technique	Synergy with AI models	Effect(s)	Interaction-oriented dimensions
Last Planner System® (LPS)	**Better forecasts** AI might quickly simulate multiple scenarios to aid project planners in establishing project lookaheads AI could learn from historical data about frequent trade problems and issue early warnings. The vast amount of information stored in previous project documents might be utilized. Transmitting knowledge and best practices can prevent information loss between projects.	**Quality** (of project lookahead, KPIs and meetings) (Better forecasts) **Quantity** (of restrictions) **Time** (project duration)	**Organizational** (Project planning) **Cultural** (LPS commitment culture)
Takt planning and Takt control	**Better forecasts** Based on historical data and environmental parameters, AI models might estimate workload values, takt times, etc. to harmonize machine and human work cycles. AI could optimize processes and deal with complexity interdependencies between trades.	**Quality** (of process and work packages definition) **Quantity** (of work packages and takt areas automatically optimized) **Time** (project duration)	**Organizational** (Project planning)
Fail safe for quality	**Automation and assistance** Computer vision AI models could supervise the construction site identifying automatically dangerous situations and production quality losses to trigger action alerts and to document the root causes. A real-time safety and quality awareness system can be created to analyze historical data and to uncover key problems.	**Quantity** (of actions defined for improvement) **Quality** (of product)	**Strategic** (Product improvement)
Five S's	**Automation and assistance** Computer vision AI models could monitor the order and cleanliness of the workplace for maintenance and improvement.	**Quality** (of workplace) **Space** (to work)	**Cultural** (Culture of cleanliness and organization)
Increased visualization	**Automation and assistance** The AI could collect information from different sources on the project such as software, cameras, documents, sensors, etc.) to filter and display it automatically in a visual form.	**Quality** (of decision-taking process) **Quantity** (collected data and easy-to-understand KPIs) **Type** (change of information format)	**Strategic** (Decision taking)
Huddle meetings	**Automation and assistance** AI could enable huddle meetings with a computer vision or speech recognition-based attendance system. AI may examine participant calendars using NLP to determine user activity trends and offer the most convenient time slots for recurring meetings. It may find available slots in large teams faster than rule-based systems (e-mail clients), allowing instant problem-solving meetings.	**Quantity** (more communication instances) **Time** (shorter meetings) **Quality** (of communication)	**Cultural** (Efficient meetings) **Community** (Communication)
First run studies (PDCA Cycle)	**Better forecasts** In the PDCA cycle, AI can support the planning phase of a new measure by simulating various scenarios and by proposing several measure alternatives. For the check phase, AI could automate data capture and analysis for a faster and more reliable evaluation of the implemented measure.	**Quantity** (more measure alternatives) **Time** (shorter check phase) **Quality** (more reliable check phase) **Quality** (data-driven measure evaluation in the check phase)	**Strategic** **Cultural** **Organizational** **Community** (Improvement measures can be carried out in all dimensions)

THE AI -DRIVEN CIP FRAMEWORK

As previously stated, LC and AI implementations can promote virtuous cycles of CIP, and they can complement and strengthen one another.

Figure 3 depicts these cooperative ties between the two systems when they are implemented in parallel: **Lean implementation in construction projects can work as the ignition for AI adoption**. Because Lean is inherently data-driven, it generates process tracking and **project documentation that may be used to train AI systems.**

A first AI model trained with project data can offer predictions (planning suggestions, cost estimations, early detection of problems, etc.) or automate repetitive processes (detecting dangerous situations on camera footages or counting elements in construction plans). These **AI-based automation and assistance solutions will free people from repetitive or complex tasks**, giving them more time for value-adding activities. This will attract more people to use AI solutions, which will enhance data generation. Also, more people will be encouraged to continue utilizing Lean methods to track and document project progress and **generate more high-quality data, as it will be structured and pre-processed in the form of KPIs.**

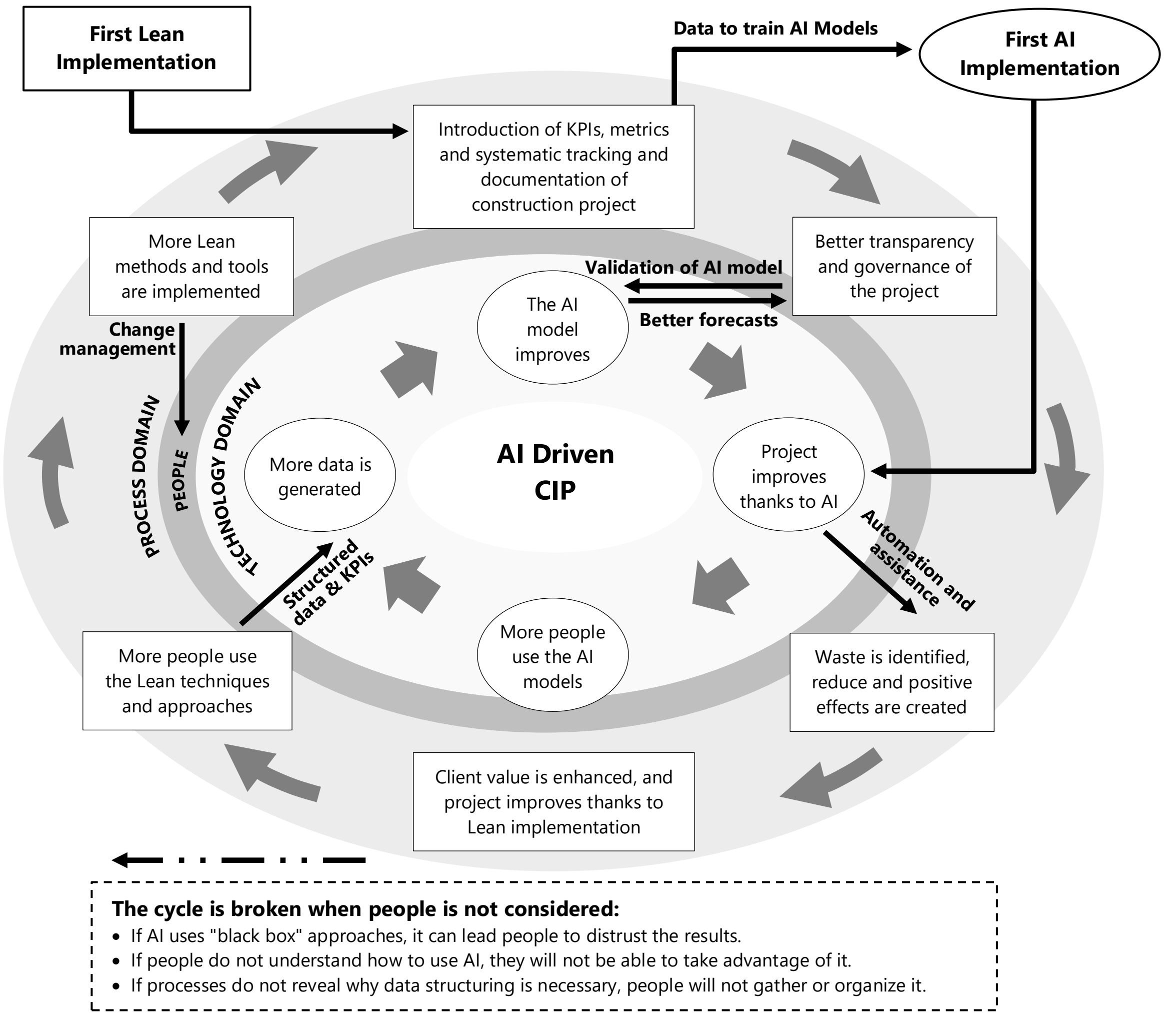

Figure 3: The AI -Driven CIP Framework

Additional and better data will improve the AI model. This will lead to **more accurate forecasts** and outcomes for AI services, which will further enhance the implemented Lean

techniques for project tracking and control. Reciprocally, this increased transparency and control over the project **will enable evaluation and validation of the AI models** by correcting their parameters to further optimize their outcomes.

The integrated system’s success will encourage more people to embrace Lean techniques, sparking a new virtuous cycle and causing another loop evolution. By using more Lean techniques, a holistic change management approach can be created that incorporates both LC and AI. **Change management focuses on people, who will be the fundamental pillar to keep these two circles of continuous improvement running**, as they will hold the system culturally and supply it data. **Because humans constitute system's core, this is where the cycle could collapse.** If people do not trust the outcomes of AI, do not grasp how to use AI systems, or do not understand the potential added value that may be gained by collecting data through LC techniques, the system will lack the vital support it requires to spread and grow.

CONCLUSIONS

The study was able to address the primary research questions. Firstly, numerous synergies between the two approaches have been identified that promote added value and growth in both directions. These synergies were discovered purely via the lens of the constituent elements of AI and Lean proposed by Guo (2017) and Salem et al. (2006), respectively. Additional synergies are likely to be discovered if secondary factors from both domains are investigated as well and demonstrated through case study observations. Secondly, it was concluded that the role of people plays a fundamental role in this symbiotic cooperation. When detecting synergies using the Ehrensberger model, it was discovered that human interaction was always present in the dimensions of interaction proposed by the method. Thus, when synthesizing the information gathered in the "AI Driven CIP" framework, people were elevated to a pivotal position as a unifying element between the two fields. Due to the centrality of the human factor in this hybrid system, potential threats that could interrupt virtuous circles of continuous improvement were recognized there.

Exactly in this area do AI systems require improvement. Many AI models are not human-centric (e.g., "black box" approaches often do not involve people). This, together with the lack of awareness about this new technology, has fueled the fear of many, for instance, of losing their own jobs. However, it should be noted that Lean's detractors have also expressed the same concerns as a result of its deployment. Therefore, Lean and AI have much more in common than at first glance, this shortcoming can be transformed into a virtue, as Lean has had several years of experience solving this problem by developing change management and acceptance of new ways of working in people.

Data play a key role in the proposed framework. AI needs data. As Lean generates it, the exchange of data serves as the main synergy between both systems. However, there are limitations to be weighed. A substantial quantity of high-quality data is required for AI to produce desirable outcomes. If the framework is used in only one project, AI will not be able to deliver usable results in early stages, due to a lack of training data. In contrast, if an excessive amount of data is provided, the model may be overtrained, hence diminishing its prediction potential (overfitting). If data from separate projects are utilized, there is also the possibility that the algorithms will be trained in distinct contexts, losing the consistency of the results. All these required refinements underline once more the central role that people play in the framework's operation, as only humans can prepare the correct data for AI training and validate its outcomes.

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